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# EQUITY MARKETS' CLUSTERING AND THE GLOBAL FINANCIAL CRISIS

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# Equity Markets' Clustering and the Global Financial Crisis[1]

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Abstract

The effect of the Global Financial Crisis (GFC) has been substantial across markets and countries worldwide. We examine how the GFC has changed the way equity markets group together based on the similarity of stock indices' daily returns. Our examination is based on agglomerative clustering methods, which yield a hierarchical structure that represents how stock markets relate to each other based on their cross-section similarity. Main results show that both hierarchical structures, before and after the GFC, are readily interpretable, and indicate that geographical factors dominate the hierarchy. The main features of equity markets' hierarchical structure agree with most stylized facts reported in related literature. The most noticeable change after the GFC is a stronger geographical clustering. Some changes in the hierarchy that do not conform to geographical clustering are explained by well-known idiosyncratic features or shocks.

Keywords: clustering, unsupervised learning, stock market, connectedness

JEL Codes: C38, L22, G15

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## 1 Introduction

The Global Financial Crisis (GFC) underscored the importance of financial *interconnectedness* for financial stability. Many economies have been affected by external shocks originating from advanced economies, which faced a particularly adverse environment characterized by high volatility. Even though sound macroeconomic fundamentals allowed some countries to withstand the shocks, the interdependence among financial markets became a key factor of the crisis and its aftermath. In this vein, *interconnectedness* and *interdependence* have become fundamental concepts to understand the nature of the crisis. Consequently, these two concepts have served policy makers and researchers to support the design and implementation of macro-prudential policy measures worldwide.[6]

In this paper we investigate financial interconnectedness with a focus on equity markets dynamics, before and after the GFC. Our aim is to examine the hierarchical structure of world equity markets in order to disentangle how this structure reveals differences among distinct regions and countries in terms of their interdependence, and how such interdependence changed with the GFC.

It is not easy to specify and assess financial interconnectedness with conventional structured models and estimation methodologies: the network of connections among equity markets is of a complex nature, which makes traditional approaches impractical and restricted. Accordingly, we estimate the network of connections among eighty stock market indices as a comprehensive measure of the dependence or interconnectedness of world equity markets. Afterwards, based on an agglomerative clustering approach, we are able to visualize and identify the hierarchical structure of equity markets around the world, before and after the GFC, with the minimum of assumptions. The hierarchical structure provides a basic but meaningful map of interdependencies among equity markets that may sharpen our understanding of financial markets' connectedness.

Interpreting this map of interdependencies will reveal some of the factors that determine equity market connectedness, in which the geographical factor has been well-documented as the most influential (see Coelho et al. (2007) and Eryigit and Eryigit (2009)). This map may also help us to identify equity markets whose strong interdependencies could provide a powerful contagion channel amid financial shocks, along with those whose behavior reveals the preeminence of

[6] For instance, interconnectedness is one of the five factors commonly used to assess systemic importance, as suggested by BCBS (2013). Furthermore, *non-substitutability* is another systemic importance factor quite related to interconnectedness. Different *higher loss absorbency requirements* (i.e. an additional buffer in the form of common equity) will be imposed based on systemic importance to reduce further the probability of failure of systemically financial institutions.

idiosyncratic factors. As we examine equity market interconnections before and after the GFC, our maps will serve to study whether (and how) equity markets' interdependencies were affected by the crisis.

Our work adds, contrasts, and updates literature on the hierarchical structure of world equity markets. By implementing an agglomerative clustering approach to examining the interdependencies among equity markets we add to prior works on the subject, which are based on other methods such as *minimal spanning trees* (see Bonanno et al. (2004), Coelho et al. (2007), and Eryigit and Eryigit (2009)) or *asset graphs* (see Sandoval (2013)). Moreover, unlike prior works, we avoid correlation-based measures of distance by using Euclidean distances, which minimize the assumptions in our approach. Our results serve the purpose of contrasting what may be considered as stylized facts from related literature, in which the geographical interdependence factor is perhaps the most recurrent finding. Also, by examining and comparing two periods, before and after the GFC, we update existing literature, which is mainly circumscribed to before the crisis (see Bonanno et al. (2004), Coelho et al. (2007), and Eryigit and Eryigit (2009)), with the exception of Sandoval (2013). Furthermore, our work adds to the literature on how the GFC affected other financial networks, such as cross-border banking networks (see Minoiu and Reyes (2013)), international syndicated loans (see Hale (2012)), or cross-border debtor-creditor relationships in equities and debt (see Chinazzi et al. (2013)). Besides, our results are useful to contrast how the hierarchical structure diverges according to the underlying market, say sovereigns' bonds (see Gilmore et al. (2010)), sovereigns' credit default swaps (see León et al. (2014)), and currencies (see Mizuno et al. (2006) and Naylor et al. (2007)).

## 2 Literature review

Our paper hinges on two growing strands of literature, on financial connectedness and on the study of the hierarchical structure of financial markets. About financial connectedness, literature may be classified into two main categories (see Kara et al. (2015)): network approaches and non-network approaches. Network approaches use pairwise relationships between financial agents (e.g. institutions, markets, countries) as an input in the analysis of connectedness in the form of a network graph, whereas non-network approaches use different techniques to estimate connectedness (e.g. principal component analysis, regression analysis, default models). Recent literature on financial networks vindicates that the network structure matters for transmission mechanisms of global financial shocks and systemic risk (see Georg and Minoiu (2014), Elliott et al. (2014), Acemoglu et al. (2015)). Our paper is based on a network approach.

In turn, broadly speaking, financial networks can be again divided into two types: direct networks and indirect networks (see Kara et al. (2015)). Direct networks use raw (i.e. observed) data from financial exposures or flows to establish connections between network participants, whereas indirect networks infer connections from prices' interdependences. As we infer equity market interdependences from stock market indices, our work may be classified as an indirect network approach.

A simple and non-exhaustive classification of indirect network approaches to examine interconnectedness consists of three different types: variance decomposition (as in Diebold and Yilmaz (2014)), Granger causality (as in Brunetti et al. (2015)), and hierarchical structure. Our approach pertains to the latter, in which we attempt to identify and examine the topological arrangement that better captures the hierarchical structure of the indirect network.

The hierarchical structure of the underlying network may be obtained by several methods, with three well-known approaches: minimal spanning trees, asset graphs, and clustering analysis.[7] All three approaches rely on estimating the dissimilarity or distance among time-series (i.e. network participants). Minimal spanning trees consist of choosing the minimal weights (i.e. shortest distances) of a connected system of all $n$ participants in such a way that the resulting system is an acyclic network (i.e. with no loops) connected by $n-1$ links that minimize the system's weight (see Onnela et al. (2003) and León et al. (2014)).[8] An asset graph is a network of distances between participants in which the number of connections is restricted by setting a threshold for what a strong link is, thus, unlike minimal spanning tress, there may be non-connected participants and loops (see Onnela et al. (2003)).[9] As will be addressed in a subsequent section, the third type, hierarchical

[7] There are other methods beyond the three reported here, such as *planar maximally filtered graphs* (see Tumminello et al. (2005)) or *clique percolation* (see IMF (2012)). An exhaustive revision of related methods is not intended in our article.

[8] Mantegna (1999) is credited for first studying the hierarchical structure of financial data (i.e. the US stock market) by means of minimal spanning trees. Afterwards, other markets have been studied by means of minimal spanning trees, such as foreign exchange markets (see Mizuno et al. (2006) and Naylor et al. (2007)), and credit default swaps (see Marsh and Stevens (2003) and León et al. (2014)).

[9] Studying the hierarchical structure of financial data by means of asset graphs is less common than by minimal spanning trees. To the best of our knowledge, Onnela et al. (2003) introduces asset graphs for examining the US stock market.

clustering, is an *exploratory data analysis approach*[10] that looks for groups (i.e. clusters) in data based on the dissimilarity among participants.

Consequently, our research may be classified as an examination of world equity markets' connectedness from a network approach, in which we employ hierarchical structure analysis on a network inferred from market data (i.e. an indirect network approach). Diagram 1 summarizes our taxonomy of related literature, and exhibits (in bold) where our article fits in.

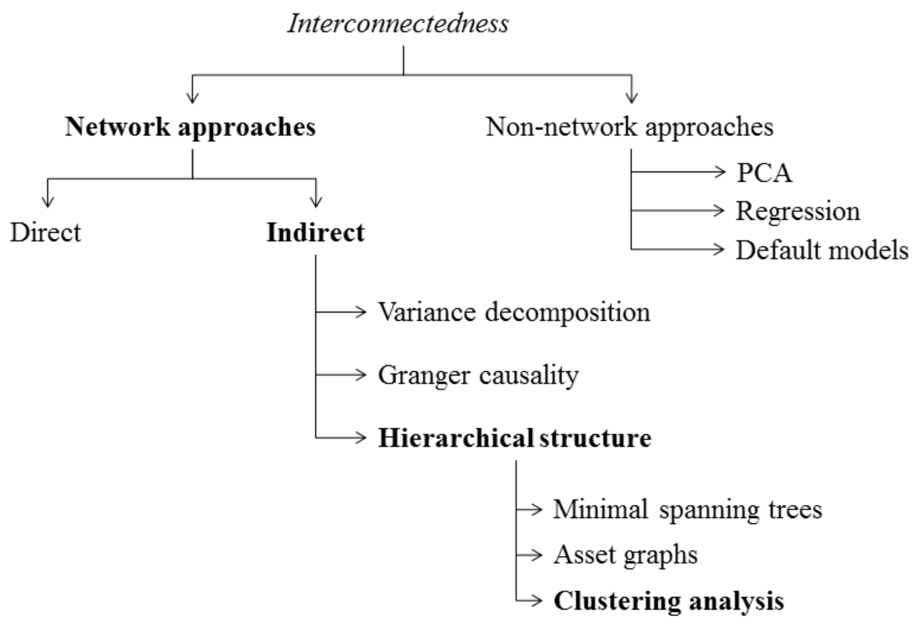


Diagram 1. Taxonomy of related literature. This is a modified version of the taxonomy suggested in Kara et al. (2015).

Most research on the hierarchical structure of world equity markets is based on *minimal spanning trees* (see Bonanno et al. (2004), Coelho et al. (2007), Gilmore et al. (2008), and Eryigit and Eryigit (2009)). Sandoval (2013) uses *asset graphs*, whereas Panton et al. (1976) uses hierarchical clustering on a limited number of equity markets. All these references work on the transformation of correlations into distances introduced by Mantegna (1999). They all find evidence of geographical organizing principles, which may encompass political, trade, historical, and cultural factors as well. Geographical clustering has also been documented as a dominant factor for sovereigns' bonds (see Gilmore et al. (2010)), sovereigns' credit default swaps (see León et al.

[10] As in Martínez & Martínez (2008), exploratory data analysis is the philosophy that data should first be explored without assumptions for the purpose of discovering what they can tell us about the phenomena we are investigating; it is a collection of techniques for revealing information about the data, and methods for visualizing them, to see what they can tell us about the underlying process that generated it.

(2014)), and currencies (see Mizuno et al. 2006). As emphasized by Krugman (1996) and Fujita et al. (1999), geographical clustering or agglomeration is by no means casual: It is a key –but often neglected- factor in the study of economic activity.

## 3 Agglomerative clustering

Clustering is an exploratory data analysis approach that looks for a particular type of structure in the data: groups (Martínez & Martínez, 2008). Under the assumption that the data represents features that would allow distinguishing one group from another, a clustering procedure organizes a set of data into groups of observations (i.e. clusters) that are more similar to each other than they are to observations belonging to a different group (Martínez et al., 2011). As depicted by Panton et al. (1976), the aim of cluster analysis is discovering the similarity relationships among the individual entities within a data set. Likewise, Halkidi et al. (2001) states that the main concern in clustering is to reveal the organization of patterns into "sensible" groups, which allows to discover similarities and differences, and to derive useful conclusions about them. As the clustering algorithm discovers by itself how the data may be organized, a clustering problem is considered an *unsupervised learning* problem (Sumathi & Sivanandam, 2006).

Two basic clustering methods are commonly used: agglomerative clustering and $k$-means clustering.[11] They both serve the purpose of organizing a dataset into groups based on how similar observations are in cross-section. Their most salient difference relates to whether the number of groups should be specified (or not): Agglomerative clustering does not require specifying the number of groups, whereas $k$-means does.

In agglomerative clustering methods we start with $m$ groups (one observation per group) and successively merge the two most similar groups until we are left with one group only (Martínez & Martínez, 2008).[12] The result of agglomerative clustering methods is a hierarchical structure that represents how observations relate to each other based on their cross-section similarities. The more similar, the closer they are in the hierarchy. The resulting structure is constrained to be hierarchical

[11] Other –more complex- clustering methods are available (e.g. fuzzy clustering, model-based clustering, spectral clustering). These other methods are described in Martínez and Martínez (2008), Kolaczyk (2009), and Martínez et al. (2011).

[12] Divisive clustering methods exist as well. Unlike agglomerative ones (i.e. bottom-up), divisive starts with a single group containing all observations and successively split the groups until there are $m$ groups with one observation per group (i.e. top-down). As reported by Martínez and Martínez (2008), divisive methods are less common.

because the groups or clusters can include one another, but they cannot intersect (Witten et al., 2011).

The hierarchical classifications produced by agglomerative clustering are represented by a two-dimensional diagram known as a *dendrogram or tree diagram*, which illustrates the successive merges made at each stage of the procedure (Everitt et al., 2011). As the resulting hierarchy contains the entire topology of the observations' grouping, it allows unveiling how the data is classified as the number of groups varies –from a single group to $m$ groups, or viceversa.

The key in agglomerative clustering is the selection of a dissimilarity measure. Distances are used as measures of dissimilarity, in which small (high) values correspond to observations that are close (distant) to (from) each other. Let $x_{iw}$ be the $w$-th element (e.g. the $w$-th return) of the $i$-th observation (e.g. the $i$-th stock market index), the most commonly used measure of distance between two series $i$ and $j$ (e.g. stock market indices) is their Euclidean distance, $d_{ij}$:[13]

$$d_{ij} = \sqrt{\sum\nolimits_{w} \left(x_{iw} - x_{jw}\right)^2} \qquad [1]$$

Similarity between stock market indices $i$ and $j$ as in [1] is calculated using all the returns. No assumption is made about the empirical distribution of returns, as is the case when using correlation as a measure of distance.[14] The distance between two stock markets $i$ and $j$ is ultimately determined by the sum of the distances between $i$ and $j$ for each $w$-return. If all $w$-returns are strictly the same for two stock market indices $i$ and $j$, then $i = j$ and $d_{ij} = 0$. Also, as a byproduct of the square of differences, $d_{ij} = d_{ji}$ (i.e. dissimilarity between stock market indices is symmetric). Finally, with respect to a third stock market index $g$, the distance between $i$ and $j$, $d_{ij}$, should be lower or equal than the sum of distances $d_{ig}$ and $d_{gj}$ (i.e. $d_{ij} \leq d_{ig} + d_{gj}$).

As usual when estimating other types of similarity measures (e.g. correlation), the indicators are transformed (i.e. standardized) before calculating the distance $d_{ij}$. This is done by means of

[13] Euclidean distance is the most often used for continuous data because of its simplicity and interpretability as a physical distance. However, other measures of distance exist as well (see Martínez and Martínez (2008) and Everitt et al. (2011)), including some transformations of the correlation coefficient.

[14] Using correlation not only requires making an assumption about the normal distribution of returns, but also may be misleading due to the positive bias in estimated correlation coefficients introduced by volatility (see Forbes and Rigobon (2002)). Hence, distances based on correlation may be biased downward with market volatility, and comparisons between different periods (with different volatilities) may be misleading.

subtracting their corresponding mean and dividing by their corresponding standard deviation, as in a customary z-score. This serves the purpose of avoiding issues related to differences in scale or dispersion of data (see Martínez et al. (2011)). After this transformation the mean and standard deviation of all indicators are 0 and 1, respectively.

If there are $n$ observations (i.e. stock market indices) the pairwise dissimilarity between observations is often presented as a $n \times n$ square matrix, which is commonly known as an interpoint distance matrix. Let $D$ be an interpoint distance matrix based on a Euclidean distance, $D$ is squared and symmetrical:

$$D = \begin{pmatrix} 0 & d_{1,2} & \cdots & d_{1,n} \\ d_{2,1} & 0 & \cdots & d_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ d_{n,1} & d_{n,2} & \cdots & 0 \end{pmatrix} \qquad [2]$$

In agglomerative clustering methods we start with $m$ groups (one observation per group) and successively merge the two most similar groups (i.e. the less distant) until we are left with one group only. As expected, the similarity criterion for merging groups is based on distance. However, measuring the distance between groups comprising several observations is different from measuring the distance between individual observations. For example, the distance between two groups may be measured as the distance between the closest observations from each group, or as the distance between the most distant, or as an average distance from all observations in each group.

The way the distance between groups or clusters is calculated is known as the linkage method. Several linkage methods are available (see Everitt et al. (2011) and Martínez et al. (2011)). The simplest method is *single linkage*, also known as *nearest neighbor* method. It uses the smallest distance between two observations, each pertaining to a different group. Let $\tilde{d}_{pq}$ be the distance between two groups or clusters $p$ and $q$, and $d_{x_{pi}x_{qj}}$ the distance between observation $i$ from group $p$ and observation $j$ from group $q$, the single linkage method is calculated as in [3].

$$\tilde{d}_{pq} = min\left\{d_{x_{pi}x_{qj}}\right\} \qquad i = 1, \dots, n;\ j = 1, \dots, n \qquad [3]$$

*Complete linkage*, also known as *furthest neighbor* method, consists of using the maximum distance between two observations, each pertaining to a different group. Therefore, instead of calculating the minimum (as in [3]), complete linkage calculates the maximum. *Average linkage* uses the average distance from all observations in group $p$ to all observations in group $q$, and it is calculated as in [4], in which $n_p$ denotes the number of observations in cluster $p$.

$$\tilde{d}_{pq} = \frac{1}{n_p n_q} \sum_{i=1}^{n_p} \sum_{j=1}^{n_q} d_{x_{pi} x_{qj}} \qquad [4]$$

*Centroid linkage,* also known as *mean distance* method, measures the distance between clusters as the distance between the means of observations in each cluster (i.e. between the average observation of each cluster). Let $\bar{p}$ and $\bar{q}$ denote the mean estimated on the observations of clusters $p$ and $q$, respectively, centroid linkage is calculated as in [5].

$$\tilde{d}_{pq} = d_{\bar{p}\bar{q}} \qquad \bar{p} = \frac{1}{n_p} \sum_{i=1}^{n_p} x_{pi} \qquad [5]$$

Diagram 2 illustrates how these four basic linkage methods work in the case of two clusters, each one containing three observations. From left to right, the linkage methodologies are single (a.), complete (b.), average (c.), and centroid linkage (d.). The discontinuous lines illustrate how the distance is calculated in each case.

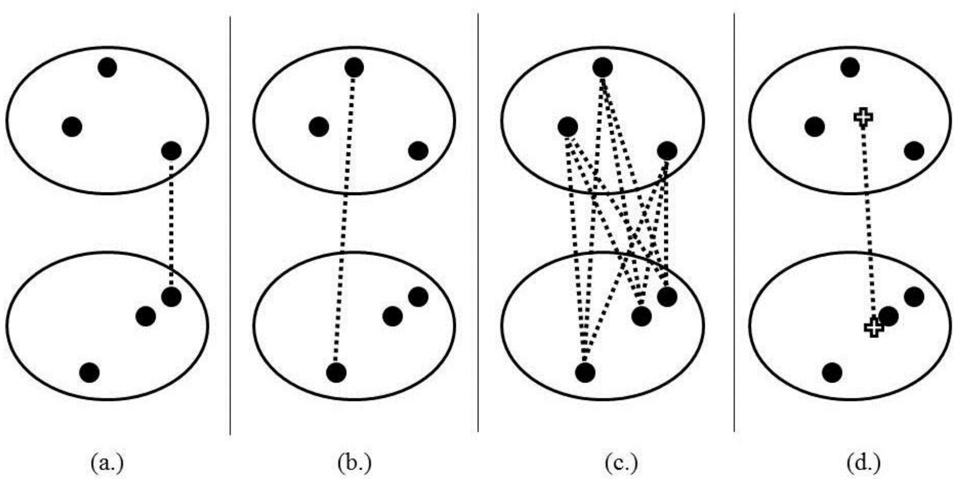


Diagram 2. Single (a.), complete (b.), average (c.) and centroid linkage (d.) methods. The cross in the centroid linkage method corresponds to the average observation estimated for each cluster.

Ward (1963) realized that the linkage problem could be better described with an objective function that minimizes the loss of information caused by merging two groups into a single one. Ward's choice for such objective function is the variance of distances among observations in a group (i.e. sum of squares of distances within a group); hence, it is also known as the *minimum variance method.* As in Everitt et al. (2011), this increase in the variance is proportional to the squared Euclidean distance between the centroids of the merged clusters ($d_{\bar{p}\bar{q}}$), but it differs from the centroid method in that centroids are weighted by $n_p n_q / \left(n_p + n_q\right)$ when computing distances between centroids, as in [6].

$$\tilde{d}_{pq} = \frac{n_p n_q {d_{\bar{p}\bar{q}}}^2}{\left(n_p + n_q\right)} \qquad [6]$$

Each linkage method has its own shortcomings (see Martínez et al. (2011) and Everitt et al. (2011)). Single linkage suffers from *chaining*: Clusters that are dissimilar tend to be merged because of in-between outliers (i.e. "noise" observations), thus the clusters are not robust, they may not be meaningful, and may be difficult to interpret. Complete linkage does not suffer from chaining, but it is sensitive to outliers, and tends to find compact clusters with small diameters. Single and complete linkage methods disregard clusters' structure.[15] Average linkage, centroid linkage, and Ward's linkage do not suffer from chaining, and they take account of the cluster structure. Average linkage is relatively robust, but tends to join clusters with small variances. In centroid linkage the more numerous of the two groups dominates the merged cluster. Ward's linkage method appears to work well but tends to find same-size, spherical clusters, and may be also sensitive to outliers.

The choice of a linkage method should pursue the validity of the clustering solution. Such validity is commonly assessed by measuring how *compact* and *separated* the clusters are. As in Halkidi et al. (2001), clustering methods should search for clusters whose members are close to each other (i.e. compact) and well-separated. A widely used clustering validity criterion is the Calinski and Harabasz (1974) clustering validity index, which is the ratio of the between-cluster sum of squares (i.e. separateness) to the within-cluster sum of squares (i.e. compactness); the larger the index the better the clustering solution. As displayed in Figure 4 (in Appendix B), Ward's attains the highest

[15] This is evident in Diagram 2. As long as the closest (farthest) elements in each cluster are preserved, single (complete) linkage method would yield the same distance between clusters irrespective of the organization of the remaining elements. On the other hand, changes in the organization of the remaining elements in average and centroid linkage methods affect the distance between clusters to some extent.

Calinski and Harabasz index, before and after the GFC. Therefore, Ward's linkage method is confirmed as our preferred linkage method [16].

Moreover, as interpretability is a vital criterion in empirical studies (see Everitt et al., (2011)), Ward's linkage method is a convenient choice because the others (i.e. single, complete, average) do not attain a meaningful hierarchical structure (see Figure 5 in Appendix C). Therefore, for the purpose of this article we report and analyze the results attained with Ward's method.[17]

## 4 The data

We use daily data of eighty stock market indices from eighty different countries. Prior related works used datasets representing 12 (Panton et al., 1976), 51 (Bonanno et al. 2004), 53 (Coehlo et al., 2007), 21 (Gilmore et al., 2008), 59 (Eryigit & Eryigit, 2009), and 91 (Sandoval, 2013) countries. We limited the number of stock markets in our dataset to eighty countries after discarding some indices that were incomplete or with gaps.

Our dataset contains stock market indices from January 10, 2005 to June 22, 2012, corresponding to to 1941 observations per country. The first sample, before the GFC, covers the January 10, 2005 – August 29, 2008 period. The second sample covers the November 3, 2008 – June 22, 2012 period. We deliberately exclude September and October 2008 data in order to prevent the exceptional volatility during the peak of GFC's turmoil from affecting our results in an unintended manner. We use similar sized samples in order to make distances comparable.

As we focus on examining stock markets' hierarchical structure, data is expressed in local currency terms, as in Eryigit and Eryigit (2009), Gilmore et al. (2010), and Sandoval (2013). Unlike Coelho et al. (2007), we are not interested in the perspective of an international investor, but in the topology of equity markets only. Moreover, it is most likely that an international investor could hedge currency risk if his aim is equity markets exposure alone.

[16] To the best of our knowledge, there are no empirical studies that examine which linkage method is better for our case (i.e. financial time series). However, consistent with results obtained with the Calinski and Harabasz index, unrelated empirical studies tend to favor Ward's linkage method (see Milligan and Cooper (1987), Ferreira and Hitchcock (2009), Everitt et al. (2011), and Hossen et al. (2015)).

[17] Dendrograms obtained with other methods (see Figure 5 in Appendix C) are not easily interpretable as they do not produce clear clusters. However, visual inspection reveals that they do not contradict the results attained with Ward's method.

The stock markets included are representative of the world's equity trading, even though the set of countries included is not exhaustive. Selected equity markets represent all regions of the globe as classified by the World Bank's lending groups. The regions, the acronyms and the number of countries represented in our data are the following: North America (NAm, 2), Latin America (LAm, 9), Europe & Central Asia (E&CAs, 37), Middle East & North Africa (ME&NAf, 10), Sub Saharan Africa (SSAf, 5), East Asia & Pacific (EAs&P, 14), and South Asia (SAs, 3). The list of countries represented, the corresponding ISO three-letter code, the Bloomberg ticker, and descriptive statistics for the eighty selected stock indices are presented in Table 1 in Appendix A.

As usual, some adjustments were executed on raw data with the aim of preventing our results and analysis from being altered by differences in country's holidays, stock market's opening and closing times, and indices' differences in scale and dispersion. First, for non-trading days we used the same closing quotes registered in the preceding day so as to avoid gaps in the series. Afterwards, defining $P_t$ as the closing price of an index at day $t$, we computed stock markets' returns as a continuous percent change of the stock market index, obtained as the logarithm of the first–difference of an index's closing quotes ($r_t = \log(P_t/P_{t-1})$).

Studies based on world stock returns data may be biased by international holidays. To correct for this potential bias we excluded those days in which more than 20% of the series (corresponding to 16 countries) had returns equal to zero. After this adjustment, our data set was reduced from 1941 to 1811 observations per market.

Likewise, we also correct for the potential distortions that the differences in countries' time zones may have on results. This problem is particularly serious when using daily (or intra-day) market data from countries with distinct opening and closing times; that is, when data is non-synchronous. We deal with the time zone problem computing rolling-average two-day returns, which is a standard procedure in previous related studies (see Forbes and Rigobon (2002)).[18]

Finally, we take care of indices' differences in scale and dispersion. If variables are measurements along different scales or if variables' standard deviations are different from one another, then one variable might dominate the distance in our calculations (Martínez et al., 2011). As expected from the different economic environments they pertain to, Figure 1 (and Table 1 in the Appendix) shows

[18] Several methods have been used to deal with the time zone problem (see Olbrys, 2013). Besides the rolling average two-day returns (Forbes and Rigobon, 2002), some of them switch to another frequency (e.g. weekly or monthly data), or take a certain hour in a leader market to register the quotes of all stock markets in the sample, whereas others use specific data-matching procedures based on opening and closing prices. Lagging indices based on the second eigenvector of the distance matrix is also possible (see Sandoval (2013)).

that differences in scales (i.e. mean) and standard deviations between the two samples and across variables (i.e. stock indices) are non-negligible. Between samples, it is evident that before the GFC the mean returns are higher and the standard deviations lower. Across stock indices, it is clear that the mean and standard deviations are different –even within the same period.

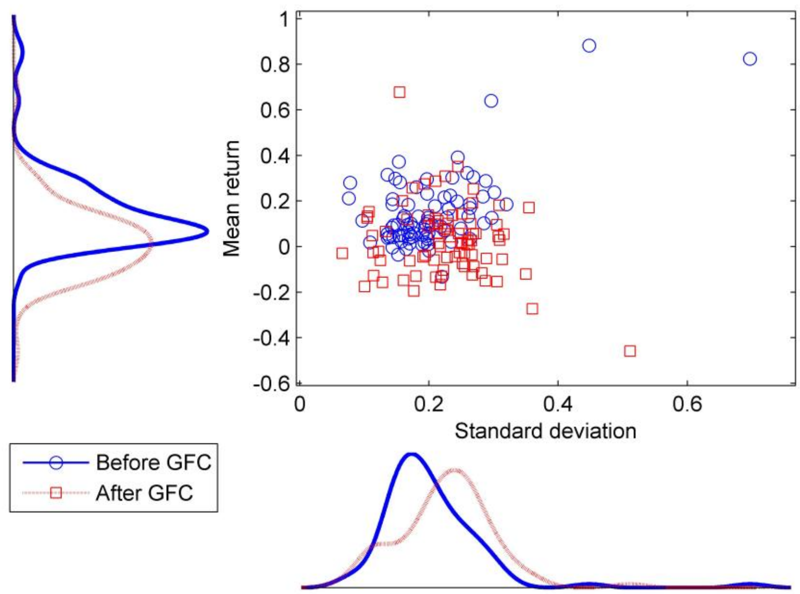


Figure 1. Scatter plot and distribution of mean and standard deviation of stock indices returns before and after the GFC. Mean and standard deviation are annualized customarily, with a 250-day basis. As expected from the different economic environments they pertain to, differences in means and standard deviations are non-negligible.

As suggested by Martínez et al. (2011), we compute the individual z-scores for each stock index, for each sample period. This procedure consisted in subtracting from each single return the average value of the returns for the sample period, and dividing it by its standard deviation.

## 5 Main results

The hierarchical classifications produced by agglomerative clustering are represented by a *dendrogram or tree diagram*, which illustrates the successive merges made at each stage of the procedure (Everitt et al., 2011). We use horizontal dendrograms, in which the successive merge of clusters appear from right to left, with the horizontal axis representing the Euclidean distance (i.e. dissimilarity) between clusters.

This section is divided in three subsections. First, we describe the dendrograms corresponding to both samples, before and after the GFC. Second, we compare the hierarchies in the dendrograms with results reported in related research works. Third, we briefly examine how the hierarchical structure of equity markets changed after the GFC.

### 5.1 The resulting hierarchies

Figure 2 presents the dendrogram corresponding to the first period (January 10, 2005 – August 29, 2008), before the GFC. From left to right, there is an initial two-branch division, corresponding to the main two clusters in the data. Cluster A contains 34 stock market indices. Most of these 34 indices in cluster A correspond to countries pertaining to Europe & Central Asia (14) or Middle East & North Africa (9); a few pertain to Latin America (3), East Asia & Pacific (3), Sub Saharan Africa (3) or South Asia (2).

Notably, most countries pertaining to Europe & Central Asia in cluster A are from Eastern Europe or Central Asia (i.e. Bosnia and Herzegovina, Bulgaria, Croatia, Estonia, Kazakhstan, Latvia, Lithuania, Montenegro, Romania, Serbia, Slovakia, Slovenia, and Ukraine); Iceland is the only country from Western Europe in cluster A, presumably because of deteriorating conditions in the banking sector before the GFC. The three stock indices from Latin America (i.e. Costa Rica, Panama, and Venezuela) may be considered particular cases due to their countries' idiosyncratic economic features.[19] Most stock indices from Europe & Central Asia in cluster A are grouped in the first sub-branch (A/A), which also includes China. Most stock indices from Middle East & North Africa are grouped in A/B/A.

[19] For instance, it is feasible that results for Panamá and Costa Rica are driven by their features as small open Central American economies with representative services sectors (e.g. tourism, financial, transport). Moreover, the lack of other stock indices from small open Central American countries may also affect the results. In the case of Venezuela, it is reasonable to conjecture that government's particular economic stance and investors' risk perception may be affecting the results. For instance, Conti and Gibert (2012) report that the Venezuelan stock market is small and closed, in which government policies and the presence of public funds in the listed companies give a special connotation to this stock market.

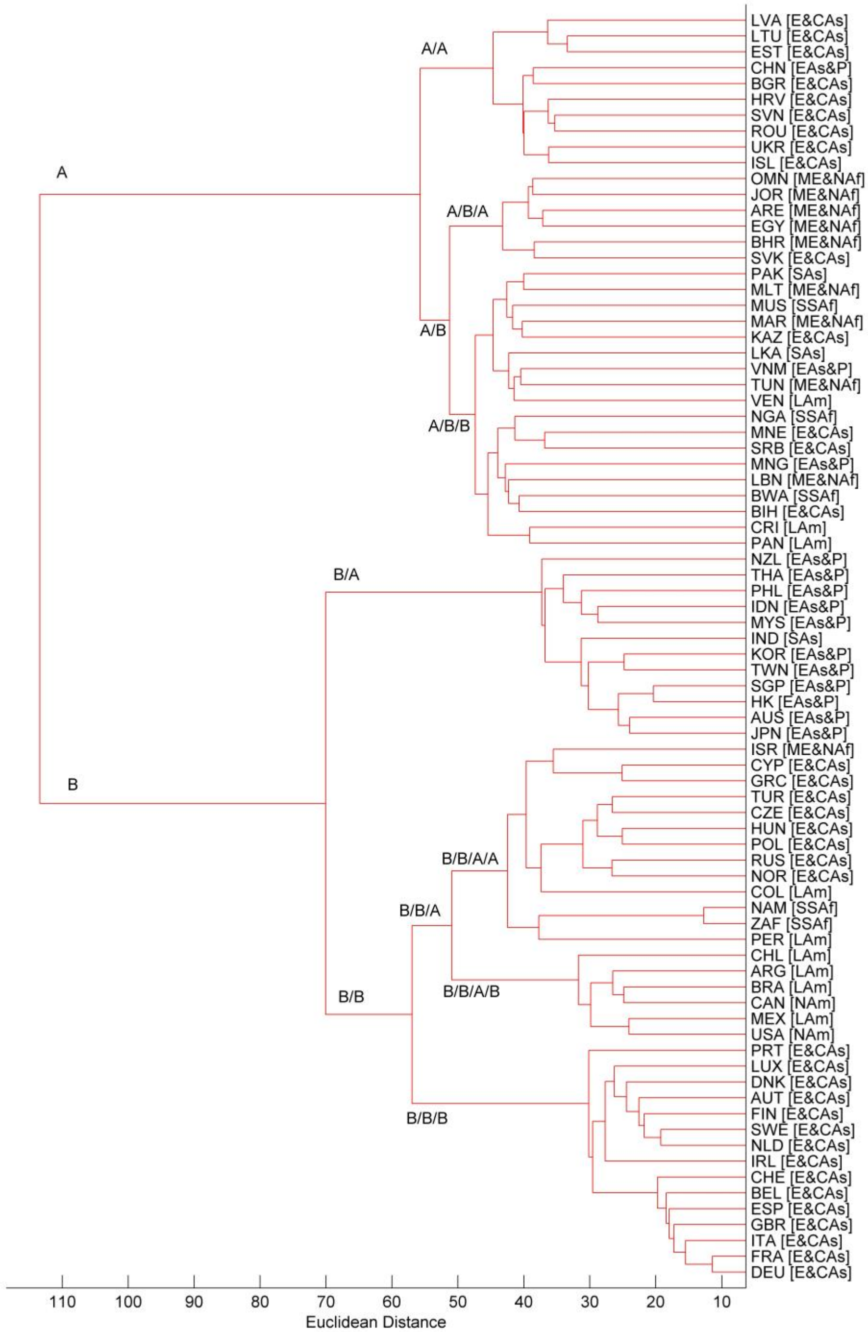


Figure 2. Dendrogram before the GFC (January 10, 2005 – August 29, 2008). In brackets the region each country pertains to according to World Bank's Lending Groups: E&CAs (Europe & Central Asia), EA&P (East Asia & Pacific), ME&NAf (Middle East & North Africa), SAs (South Asia), SSAf (Sub Saharan Africa), LAm (Latin America), NAm (North America).

The second main branch, containing cluster B, consists of the remaining 46 stock indices. Most of them correspond to Europe & Central Asia (23), East Asia & Pacific (11), and Latin America (8);

only one from Middle East & North Africa (i.e. Israel), one from South Asia (i.e. India), and two from Sub Saharan Africa (i.e. Namibia and South Africa) disrupt the geographical composition of cluster B. All East Asia & Pacific stock indices in cluster B are grouped in a single branch (B/A), which also includes India. All Western Europe stock indices are in cluster B –except Iceland-, and most of them are grouped in a single cluster, B/B/B. Eastern Europe indices in cluster B correspond to Czech Republic, Hungary, Poland, and Russia, and they are grouped in a separate cluster with Norway and Turkey; the other Eastern Europe countries are in cluster A. Mexico and the United States group together and –subsequently- they cluster with Argentina, Brazil, Canada and Chile. The two other Latin American stock indices in cluster B, Colombia and Peru, do not pertain to the American continent cluster in B/B/A/B, and they are closer to Eastern Europe and Sub Saharan market indices, respectively.

Bilateral distances between grouped stock markets indices in cluster A are noticeably lower than those in cluster B. Western Europe equity markets (in cluster B, branch B/B/B) are particularly close to each other, whereas no group of equity markets is markedly tight in cluster A. That is, interconnectedness is visibly higher in cluster B, which displays four geographical imperfect clusters corresponding to Western Europe, America, Easter Europe, and East Asia & Pacific. On the other hand, cluster A is not particularly interconnected, but also displays the importance of geographical clustering.

Figure 3 presents the dendrogram corresponding to the second period (November 3, 2008 – June 22, 2012), after the GFC. From left to right, there is an initial two-branch division, corresponding to the main two clusters in the data. Cluster A contains 48 stock market indices. Most of these 48 indices correspond to countries pertaining to Europe & Central Asia (16), East Asia & Pacific (14) or Middle East & North Africa (9); a few pertain to South Asia (3), Latin America (3), or Sub Saharan Africa (3). There is an obvious change in the number of participants in cluster A: it gains 14 stock indices, most of them from East Asia & Pacific –which pertained to cluster B (branch B/A) in the previous (i.e. pre-crisis) period.

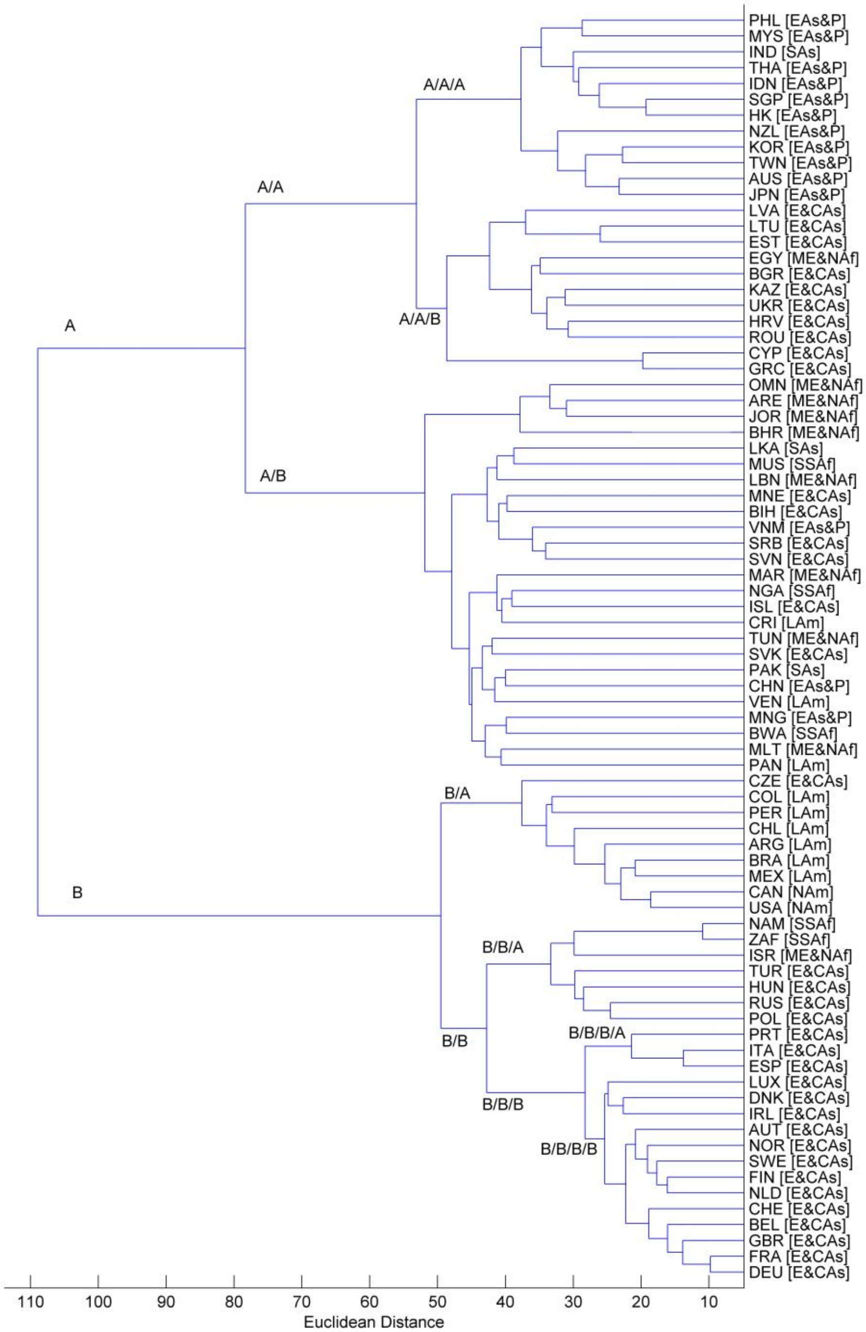


Figure 3. Dendrogram after the GFC (November 3, 2008 – June 22, 2012). In brackets the region each country pertains to according to World Bank's Lending Groups: E&CAs (Europe & Central Asia), EA&P (East Asia & Pacific), ME&NAf (Middle East & North Africa), SAs (South Asia), SSAf (Sub Saharan Africa), LAm (Latin America), NAm (North America).

Again, all countries pertaining to Europe & Central Asia in cluster A –except Iceland, Cyprus and Greece- are from Eastern Europe or Central Asia; the deteriorating banking and fiscal conditions in

Iceland, Cyprus, and Greece may explain their decoupling from their regional cluster. Latin American countries in cluster A (i.e. Costa Rica, Panamá, and Venezuela) may be –once again- considered particular cases due to their countries' intrinsic economic features. All stock indices from East Asia & Pacific (except China, Mongolia, and Vietnam) pertain to a single cluster (A/A/A) that also includes India; once more, China is decoupled from its regional cluster, presumably because of its long-lived weak integration to other stock markets (see Glick and Hutchinson (2013)). Most stock indices from Europe & Central Asia in cluster A are grouped in branch A/A/B. Most stock indices from Middle East & North Africa are in cluster A/B along others from Latin America, Sub Saharan Africa, Europe & Central Asia.

The second main branch, B, consists of the remaining 32 stock indices. Most of them correspond to Europe & Central Asia (21), Latin America (6), and North America (2); only one from Middle East & North Africa (i.e. Israel), and two from Sub Saharan Africa (i.e. Namibia and South Africa) disrupt the geographical composition of cluster B. Different from the period before the GFC, cluster B does not contain stock indices from East Asia & Pacific, and Greece and Cyprus have vanished from cluster B as well. All Western Europe stock indices are in cluster B –except Iceland, Greece, and Cyprus-, and most of them are grouped in a single cluster, B/B/B.

Once more, bilateral distances between grouped stock markets indices in cluster A are noticeably lower than those in cluster B; that is, equity markets in cluster A are more interconnected. Again, Western Europe stock markets (in cluster B, branch B/B/B) are particularly close to each other. Additionally, it is evident that after the GFC cluster B shows a well-defined and tighter Latin American cluster (B/A) containing Argentina, Brazil, Chile, Colombia, Mexico, and Peru. About cluster A, the group containing most East Asia & Pacific stock markets (i.e. A/A/A) is visibly tighter than the rest of stock markets in that cluster, but it is still less interconnected than most clusters in B.

### 5.2 Resulting hierarchies and stylized facts

Literature on the hierarchical structure of world equity markets has arrived to some well-established features that may be considered stylized facts. Perhaps the most recurrent finding is related to the geographical nature of clusters (see Bonanno et al. (2004), Coehlo et al. (2007), Eryigit and Eryigit (2009), and Sandoval (2011)). Our results concur with this stylized fact: Clusters in both samples, before and after the GFC, reveal the importance of geographic closeness. Nevertheless, it is important to realize that several similarity factors may be captured by geographic proximity, such as cultural (e.g. common language, religion), economical (e.g. development, allocation of natural resources, trade and investment partners), and political.

A second stylized fact from previous research on world stock indices is the strong cross-section similarity among the most developed (i.e. Western) European countries (see Bonanno et al. (2004), Coehlo et al. (2007), Eryigit and Eryigit (2009), and Sandoval (2011)). Our results confirm that Western Europe countries are the most similar in cross-section in both samples: Euclidean distances among Western Europe countries are the lowest in both samples, and they do not differ manifestly. An interesting finding in the dendrogram corresponding to the second sample (after the GFC) is the decoupling of Italy, Spain, and Portugal from the core of Western Europe countries. Such decoupling overlaps with the hierarchical structure of sovereigns' bonds and credit default swaps before and after the GFC (see Gilmore et al. (2010) and León et al. (2014)). It is reasonable to affirm that the GFC and the European Sovereign Debt crisis that started in 2009 coupled the equity and sovereign markets of Italy, Spain, and Portugal, which were among the most affected –along with Ireland, Cyprus, and Greece.

A third stylized fact is related to the role of the United States equity market. As stated by Coehlo et al. (2007), the United States, whose equity market is globally dominant in terms of market value, exhibits a somewhat looser linkage to other markets. Similar results may be inferred from visualizations reported by Eryigit and Eryigit (2009) and Sandoval (2013). Results in both dendrograms show that the United States is not dominant in the hierarchy of world equity markets. This may reflect that idiosyncratic factors dominate the United States equity market, whereas others –especially Western Europe markets- are easily affected by systemic factors in the form of regional interconnectedness.

A fourth stylized fact is related to the cluster of equity markets pertaining to the East Asia & Pacific region. Eryigit and Eryigit (2009) reports that integration of East Asian markets among themselves as well as to the Western markets is found to be rather weak. Coehlo et al. (2007) reports that Asian equity markets are not strongly clustered, except in 1998 –in the peak of the Asian crisis. Our results agree. In both samples the main East Asia & Pacific cluster is not as tightly connected as, say, that of Western Europe markets. This concurs with reports on how financial integration in Asia lags behind trade integration because of relatively smaller cross-border capital flows, lower banking integration, high degree of "home bias", and barriers to foreign asset holdings and foreign bank entry (see IMF (2014) and Guimaraes-Filho and Hong (2016)). Moreover, before the GFC the main link of East Asia & Pacific cluster is a non-strong connection with Europe & Central Asia and American clusters (in cluster B), whereas after the GFC its main link is also a non-strong connection with Eastern Europe markets (in cluster A). That is, the East Asia & Pacific cluster is not particularly linked to other regional clusters, and –as discussed in the next section- its linkage changed abruptly after the GFC.

Some particular cases of persistent strong bilateral similarity (i.e. low Euclidean distance in the x-axis) have been well-documented in previous research works. First, concurrent with Coehlo et al. (2007) and Sandoval (2013), the stock markets of the United States, Mexico, and Canada tend to be close in both samples, which may be a consequence of their geographical adjacency and their trade agreements (i.e. NAFTA – North American Free Trade Agreement). However, we find that Canada, Mexico, and United States do not cluster together in both samples. Before the GFC there is a strong bilateral similarity between the United States and Mexico, whereas after the crisis such similarity is between the United States and Canada; in the first (second) sample Canada (Mexico) was closer to some Latin American indices. Second, as in Sandoval (2013), the stock indices of South Africa and Namibia are tightly coupled in both samples, which may reflect their mutual economic and political dependence. Third, France and Germany tend to be strongly interconnected, as is usual in previous research works (see Coehlo et al. (2007) and Sandoval (2013)). Fourth, our results exhibit strong bilateral similarity between Greece and Cyprus, along with their disconnection from the Western Europe cluster, which overlaps with Sandoval (2013). However, our results show that the disconnection of Greece and Cyprus from Western Europe aggravates after the GFC: In the first sample Greece and Cyprus belong to a cluster of Eastern Europe stock markets that are close to America and Western Europe in cluster B, whereas in the second sample they belong to cluster A, which is far from America and Eastern Europe. The European Sovereign Debt crisis may be the reason behind the further decoupling of Greece and Cyprus from the Western Europe cluster after the GFC.

Some stock markets have been reported as consistently displaying anomalous results with respect to geographical clustering. Sandoval (2013) reports that Venezuela, Costa Rica, Panama, Iceland, and Malta tend to be loosely related to all other indices, whereas Coehlo et al. (2007) visualizations (i.e. minimal spanning trees) reveal that some of these stock markets tend to locate erratically and to disrupt geographical clustering. Irrespective of the sample, our results overlap regarding these anomalies: Venezuela, Costa Rica, Panama, Iceland, and Malta do not follow regional clustering, and some of them cluster together for no clear reason (e.g. Malta and Panama, Costa Rica and Iceland), except Panama and Costa Rica in the first sample. Israel has been reported to depart from its regional partners (Middle East & North Africa) and to group with European countries (see Eryigit and Eryigit (2009) and Sandoval (2013)); our results agree in both samples. Likewise, Peru and Colombia have been reported to display periods in which they depart from their geographical cluster (see Coehlo et al. (2007)); as depicted in the first sample's hierarchy, our results before the GFC agree, but –as discussed below- they tend to cluster together with the rest of Latin America (and America) afterwards.

China is an interesting case that has not been discussed in related literature –to the best of our knowledge. China is decoupled from its regional cluster before and after the GFC. First China pertains to a cluster conformed mainly by Eastern Europe markets, with Bulgaria as its most similar peer. Afterwards it pertains to a rather heterogeneous cluster, with Pakistan as its most similar one. Authors using non-related approaches have documented that China is a particular case of a weakly integrated equity market for several reasons, such as tight state controls over equity markets, the prevalence of large state-owned firms, limited market liquidity, and a slow liberalization of capital controls (see Masson et al. (2008) and Glick and Hutchinson (2013)). Therefore, our overall results regarding China's decoupling from regional and world markets concur with findings from other strands of literature on equity markets interconnectedness.

Some differences with prior research works are worth highlighting. For instance, our results show that Australia and New Zealand pertain to a cluster containing East Asia & Pacific and South Asia stock markets, but they do not exhibit strong bilateral closeness. Our results regarding the Australia and New Zealand overlap with those by Sandoval (2013), but contradict the hierarchical proximity reported by Coehlo et al. (2007) and Eryigit and Eryigit (2009). Also, Jordan is reported to cluster erratically, against geographical factors (see Coehlo et al. (2007) and Eryigit and Eryigit (2009)). However, concurrent with Sandoval (2013), we find that Jordan clusters according to geographical factors.

### 5.3 Changes in hierarchies after the GFC

It is clear that the resulting hierarchies are different from one period to the other. The most visible difference is related to East Asia & Pacific stock indices moving away from the cluster containing Western Europe and American stock indices to that containing Eastern Europe, Central Asia, South Asia, and Middle East & North Africa stock indices. It is feasible to state that after the GFC investors regarded East Asia & Pacific equity markets as decoupled from Western Europe and American equity markets, closer to other Asian or Eastern Europe markets. Moreover, as the differences in Euclidean distances between the East Asia & Pacific and their closest cluster reveals, this region became more interconnected to the hierarchy after the GFC. However, as previously stated, East Asia & Pacific equity markets are not particularly integrated among them or to other clusters, before or after the GFC.

It is worth noting that China did not couple with East Asia & Pacific cluster after the GFC: The relocation of the East Asia & Pacific after the GFC did reduce the distance between China and its geographical cluster, but China is still more similar to other equity markets. Such reduction in the distance between China and other Asian equity markets after the GFC has been documented under different approaches, and has been associated to its increasing importance of China for the world economy and for intra-regional trade (see Kang and Yoon (2011), and Glick and Hutchinson (2013)). Asian markets being more similar to other markets (e.g. the United States) than to China after the GFC has been documented as well (see Glick and Hutchinson (2013)). Therefore, it is fair to suggest that our results agree with evidence regarding how China has approximated its geographical cluster after the GFC but still remains somewhat decoupled.[20]

Another difference is evident in the clustering of Western Europe stock indices. Before the GFC there was no discernible clustering within Western Europe markets. After the crisis, Italy, Spain, and Portugal clustered in a group (in branch B/B/B/A) that afterwards merged with the rest of Western Europe. That is, after the GFC investors regarded Italy, Spain, and Portugal equity markets as conveying different risk factors, as is also the case with Greece and Cyprus, which moved away from Western Europe and American stock markets. As mentioned before, this may be a consequence of the European Sovereign Debt crisis.

An additional difference between both samples is related to the American cluster. Before the GFC the American cluster was integrated by Mexico, the United States, Argentina, Brazil, Canada, and Chile; as already stated, Colombia and Peru were missing from the main American and Latin American cluster. Colombia and Peru joined the American and Latin American cluster after the GFC. This may be related to the integration of the Colombian, Chilean and Peruvian stock markets and the corresponding securities depositaries amid the Latin American Integrated Market (MILA), which was agreed in 2009 but formally started in May 2011.[21] This result coincides with Mellado and Escobari (2015) in that each of these markets became more sensitive to the movements of the

[20] It has been documented that spillovers from China's stock market volatility have been significant for other Asian economies during 2015 (see Guimaraes-Filho and Hong (2016)). Thus, it is arguable that China has increasingly approximated its regional cluster after the GFC.

[21] The integration process amid MILA is of a virtual nature; there are no corporate changes (e.g. merge or acquisition), but an integration based on technological tools and regulatory standardization. The first phase of this integration process (including Chile, Colombia and Peru) started on September 8, 2009, but it was only until the end of May, 2011 that MILA formally started operations (see Mellado and Escobari (2015)). On December 2014 the entry of Mexico became official.

other two, but also in that Latin American markets exhibit an important degree of integration with the US stock market.

All in all, it is rather evident that geographical clustering augmented after the GFC. Tightly interconnected regions became more interconnected, as is the case of Western Europe and America. East Asia & Pacific, a region non-strongly interconnected with others before the GFC, relocated afterwards and strengthened their connections with their new closest cluster. Markets that experienced strong common adverse shocks clustered together, and moved away (in tandem) from their pre-GFC geographical cluster. Two specific cases of departure from geographical clustering are most marked, and they presumably correspond to the same shock (i.e. the European Sovereign Debt Crisis): Greece and Cyprus, whose bilateral interconnectedness augmented while they decoupled from their geographic cluster (i.e. Western Europe), and Italy, Spain, and Portugal, that became a separate group within the Western Europe cluster.

## 6 Final remarks

In this paper we investigate the interconnectedness of equity markets by means of agglomerative clustering, an exploratory data analysis approach that allows visualizing and identifying the hierarchical structure of eighty stock indices around the world. Our results contribute to the existing literature by means of using an alternative approach to the study of the hierarchical structure of equity markets, and by avoiding assumptions related to the customary correlation-into-distance transformation. As we examine the equity market hierarchical structure before and after the Global Financial Crisis (GFC), we also help to update and contrast related literature.

Despite our different choice of approach (i.e. agglomerative clustering) and of distance measure (i.e. Euclidean distance), our results concur with literature's most recurrent findings. For instance, we find evidence of geographical organizing principles, which result in the prevalence of geographical clustering for most of the stock indices considered. Likewise, our results concur with other most well-known features of equity markets hierarchical structure, such as the tight interconnectedness among Western Europe equity markets; the non-dominant role of United States; the weak integration of Asian markets among themselves and to other regions; the existence of several cases of strong bilateral interdependence (e.g. France and Germany, South Africa and Namibia, Greece and Cyprus); and the presence of several markets consistently displaying anomalous results (e.g. Venezuela, Costa Rica, Panama, Iceland, Malta). Some differences between our results and the literature are certainly explained by idiosyncratic features of certain countries or by the occurrence of shocks (e.g. the European Sovereign Debt crisis).

The main finding resulting from the comparison between the hierarchical structure before and after the GFC is that that geographical clustering augmented after the crisis. Tightly interconnected regions became more interconnected (e.g. Western Europe and America). Regions non-strongly connected were relocated in the hierarchy, and are now closer to their new closest cluster (e.g. East Asia & Pacific). And markets that experienced strong common shocks became tightly clustered within their regional cluster (e.g. Italy, Spain and Portugal), or strengthened their interdependence while decoupling from their regional cluster (e.g. Greece and Cyprus). These results contribute to the literature by contrasting results of the pre-GFC period.

Some challenges and avenues for future research are open. The comparison of equity markets' hierarchical structure may be expanded to include more recent data, in which the post-GFC measures by central banks (e.g. quantitative easing) in affected countries have started to be abandoned; as the return to typical monetary stances in some central banks is still incomplete, we did not attempt to include this third sample. Including exchange rate risk in the examination by expressing all indices in a *numeraire* (e.g. US dollar) may be interesting. Comparing the hierarchical structures with and without exchange rate risk may illustrate to what extent currency dynamics reinforce or moderate similarity between stock markets, and to what extent (and how) the hierarchy is affected. Regarding transmission channels, our work contributes to visualizing and analyzing how interdependent equity markets are, and to the discovery of a rationale for such interdependence. However, we do not attempt to identify and measure the significance of a comprehensive set of feasible transmission channels (e.g. geographical clustering, common shocks, trade, capital flows, and macroeconomic fundamentals). As intended in exploratory data analysis, our work successfully explores data for the purpose of discovering clues about interconnectedness among equity markets, but the validity of such clues is to be attained by usual confirmatory analysis (e.g. hypothesis testing). Finally, as there are other methods for examining the hierarchical structure of equity markets besides those here reported (i.e. minimal spanning trees and asset graphs) or implemented (i.e. agglomerative clustering), further additions and contrasts to the existing literature are readily available for future research.

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## 8 Appendix A. Basic information and statistics on selected stock indices

| Region[a] | Country | ISO Code[b] | Bloomberg Ticker | January 10, 2005 - August 29, 2008 | | | | November 3, 2008 - June 22, 2012 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | Mean | Std. Dev. | Skewness | Kurtosis | Mean | Std. Dev. | Skewness | Kurtosis |
| North America [NAm] | United States | USA | SPX | (0,00) | 0,01 | (0,18) | 5,25 | 0,00 | 0,02 | (0,42) | 7,62 |
| | Canada | CAN | SPTSX | 0,00 | 0,01 | (0,59) | 4,81 | (0,00) | 0,01 | (0,83) | 9,56 |
| Latin America [LAm] | Mexico | MEX | MEXBOL | 0,00 | 0,01 | (0,10) | 5,39 | 0,00 | 0,01 | (0,15) | 6,70 |
| | Brazil | BRA | IBOV | 0,00 | 0,02 | (0,27) | 3,87 | 0,00 | 0,02 | (0,15) | 6,36 |
| | Panama | PAN | BVPSBVPS | 0,00 | 0,00 | 1,11 | 19,09 | 0,00 | 0,01 | (2,54) | 138,86 |
| | Argentina | ARG | MERVAL | 0,00 | 0,01 | (0,40) | 4,98 | 0,00 | 0,02 | (0,34) | 6,03 |
| | Chile | CHL | IPSA | 0,00 | 0,01 | (0,47) | 7,06 | 0,00 | 0,01 | (0,45) | 8,47 |
| | Venezuela | VEN | IBVC | 0,00 | 0,02 | (2,79) | 44,89 | 0,00 | 0,01 | 0,69 | 10,93 |
| | Peru | PER | IGBVL | 0,00 | 0,02 | (0,66) | 7,38 | 0,00 | 0,02 | (0,38) | 9,72 |
| | Colombia | COL | COLCAP | 0,00 | 0,02 | (0,06) | 22,61 | 0,00 | 0,01 | (0,17) | 4,86 |
| | Costa Rica | CRI | CRSMBCT | 0,00 | 0,01 | 1,24 | 25,07 | (0,00) | 0,01 | (5,48) | 83,56 |
| Europe & Central Asia [E&CAs] | U. Kingdom | GBR | UKX | 0,00 | 0,01 | (0,30) | 6,21 | 0,00 | 0,01 | 0,03 | 7,10 |
| | Germany | DEU | DAX | 0,00 | 0,01 | (0,57) | 7,47 | 0,00 | 0,02 | (0,08) | 5,89 |
| | France | FRA | CAC | 0,00 | 0,01 | (0,42) | 6,64 | (0,00) | 0,02 | 0,06 | 6,03 |
| | Spain | ESP | IBEX | 0,00 | 0,01 | (0,52) | 9,03 | (0,00) | 0,02 | 0,30 | 7,42 |
| | Switzerland | CHE | SMI | 0,00 | 0,01 | (0,38) | 6,08 | (0,00) | 0,01 | (0,21) | 6,03 |
| | Italy | ITA | FTSEMIB | (0,00) | 0,01 | (0,51) | 5,49 | (0,00) | 0,02 | (0,17) | 5,12 |
| | Portugal | PRT | BVLX | 0,00 | 0,01 | (1,04) | 10,00 | (0,00) | 0,01 | 0,22 | 8,02 |
| | Ireland | IRL | ISEQ | (0,00) | 0,01 | (0,31) | 6,96 | (0,00) | 0,02 | (0,38) | 5,31 |
| | Iceland | ISL | ICEXI | 0,00 | 0,01 | (0,46) | 5,09 | (0,00) | 0,02 | (13,53) | 298,46 |
| | Netherlands | NLD | AMX | 0,00 | 0,01 | (0,44) | 6,60 | 0,00 | 0,02 | (0,19) | 5,05 |
| | Belgium | BEL | BEL20 | (0,00) | 0,01 | (0,31) | 6,58 | (0,00) | 0,01 | (0,01) | 5,43 |
| | Luxemburg | LUX | LUXXX | 0,00 | 0,01 | (0,09) | 6,52 | (0,00) | 0,02 | 0,05 | 4,10 |
| | Denmark | DNK | KFX | 0,00 | 0,01 | (0,47) | 5,02 | 0,00 | 0,01 | 0,08 | 5,32 |
| | Finland | FIN | HEX | 0,00 | 0,01 | 0,13 | 7,77 | (0,00) | 0,02 | (0,03) | 4,79 |

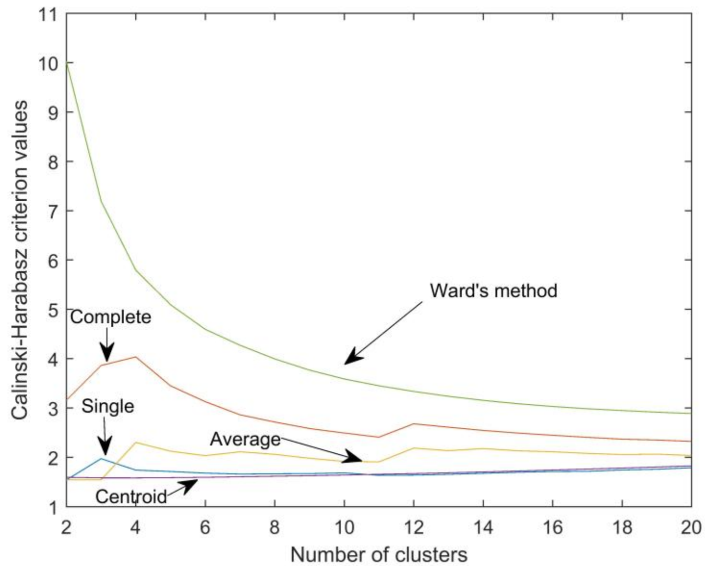
| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Norway | NOR | OBX | 0,00 | 0,01 | (0,41) | 4,84 | 0,00 | 0,02 | (0,47) | 6,88 |
| | Sweden | SWE | OMX | 0,00 | 0,01 | (0,26) | 4,95 | 0,00 | 0,02 | 0,02 | 5,73 |
| | Austria | AUT | ATX | 0,00 | 0,01 | (0,75) | 6,30 | (0,00) | 0,02 | (0,03) | 5,10 |
| | Greece | GRC | ASE | 0,00 | 0,01 | (0,30) | 7,23 | (0,00) | 0,02 | 0,31 | 5,19 |
| | Poland | POL | WIG | 0,00 | 0,01 | (0,44) | 4,93 | 0,00 | 0,01 | (0,21) | 5,60 |
| | Czech Rep. | CZE | PX | 0,00 | 0,01 | (0,24) | 8,07 | (0,00) | 0,02 | (0,10) | 5,58 |
| | Russian Fed. | RUS | CF | 0,00 | 0,02 | (0,58) | 6,54 | 0,00 | 0,02 | (0,10) | 9,18 |
| | Hungary | HUN | BUX | 0,00 | 0,01 | (0,16) | 3,80 | 0,00 | 0,02 | 0,03 | 5,75 |
| | Romania | ROU | BET | 0,00 | 0,02 | (0,09) | 5,20 | 0,00 | 0,02 | (0,53) | 9,77 |
| | Ukraine | UKR | PFTS | 0,00 | 0,02 | (0,61) | 6,48 | 0,00 | 0,02 | 0,01 | 10,08 |
| | Kazakhstan | KAZ | KZKAK | 0,00 | 0,03 | 0,54 | 8,05 | (0,00) | 0,02 | 0,96 | 23,72 |
| | Slovakia | SVK | SKSM | 0,00 | 0,01 | (0,35) | 8,84 | (0,00) | 0,01 | (2,14) | 31,51 |
| | Croatia | HRV | CRO | 0,00 | 0,01 | (0,02) | 7,29 | (0,00) | 0,01 | (0,12) | 9,31 |
| | Slovenia | SVN | SBITOP | 0,00 | 0,01 | 0,02 | 9,86 | (0,00) | 0,01 | (0,81) | 8,82 |
| | Bosnia and H. | BIH | BIRS | 0,00 | 0,01 | 0,23 | 6,59 | (0,00) | 0,01 | (0,15) | 8,60 |
| | Serbia | SRB | BELEXLIN | 0,00 | 0,01 | 1,56 | 23,42 | (0,00) | 0,01 | 0,37 | 6,94 |
| | Montenegro | MNE | MONEX20 | 0,00 | 0,02 | 0,70 | 6,82 | (0,00) | 0,02 | 1,19 | 13,28 |
| | Estonia | EST | TALSE | 0,00 | 0,01 | (0,24) | 13,79 | 0,00 | 0,01 | 0,64 | 9,44 |
| | Latvia | LVA | RIGSE | 0,00 | 0,01 | (0,17) | 8,11 | 0,00 | 0,02 | 0,39 | 7,18 |
| | Lithuania | LTU | VILSE | 0,00 | 0,01 | (0,32) | 5,53 | 0,00 | 0,01 | (0,04) | 17,20 |
| | Bulgaria | BGR | SOFIX | 0,00 | 0,01 | (0,26) | 7,22 | (0,00) | 0,01 | (0,56) | 12,35 |
| | Turkey | TUR | XU100 | 0,00 | 0,02 | (0,32) | 4,50 | 0,00 | 0,02 | (0,16) | 5,53 |
| | Cyprus | CYP | CYSMMAPA | 0,00 | 0,02 | (0,19) | 8,49 | (0,00) | 0,03 | 0,25 | 5,05 |
| Middel East & North Africa [ME&NAf] | Malta | MLT | MALTEX | 0,00 | 0,01 | 0,03 | 9,66 | (0,00) | 0,01 | 0,33 | 9,88 |
| | Egypt | EGY | CASE | 0,00 | 0,02 | (0,33) | 5,69 | (0,00) | 0,02 | (0,72) | 6,69 |
| | Morocco | MAR | MCS | 0,00 | 0,01 | (0,60) | 7,84 | (0,00) | 0,01 | (0,22) | 7,90 |
| | Tunisia | TUN | TUSISE | 0,00 | 0,00 | 0,99 | 9,23 | 0,00 | 0,01 | (0,57) | 13,72 |
| | Israel | ISR | TA-100 | 0,00 | 0,01 | (0,73) | 5,27 | 0,00 | 0,01 | (0,38) | 5,73 |
| | Lebanon | LBN | BLOM | 0,00 | 0,01 | (0,11) | 15,99 | (0,00) | 0,01 | 0,75 | 14,04 |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Bahrain | BHR | BHSEASI | 0,00 | 0,01 | 0,37 | 8,40 | (0,00) | 0,01 | (1,26) | 10,21 |
| | Jordan | JOR | JOSMGNFF | 0,00 | 0,01 | (0,08) | 6,21 | (0,00) | 0,01 | (0,29) | 6,89 |
| | Oman | OMN | MSM30 | 0,00 | 0,01 | (1,29) | 16,10 | (0,00) | 0,01 | (0,46) | 13,20 |
| | U.A.E. | ARE | DFMGI | 0,00 | 0,02 | (0,06) | 7,81 | (0,00) | 0,02 | (0,21) | 6,80 |
| Sub Saharan Africa [SSAf] | South Africa | ZAF | JALSH | 0,00 | 0,01 | (0,30) | 5,56 | 0,00 | 0,01 | 0,13 | 5,12 |
| | Namibia | NAM | FTN098 | 0,00 | 0,01 | (0,11) | 4,76 | 0,00 | 0,02 | (0,07) | 6,08 |
| | Botswana | BWA | BGSMDC | 0,00 | 0,01 | 4,96 | 89,65 | (0,00) | 0,00 | (1,58) | 36,28 |
| | Nigeria | NGA | NGSEINDX | 0,00 | 0,01 | 0,26 | 7,29 | (0,00) | 0,01 | 0,37 | 16,76 |
| | Mauritius | MUS | SEMDEX | 0,00 | 0,01 | (0,64) | 157,52 | 0,00 | 0,01 | 0,36 | 22,34 |
| East Asia & Pacific [EAs&P] | Japan | JPN | NKY | 0,00 | 0,01 | (0,42) | 4,87 | (0,00) | 0,02 | (0,60) | 7,93 |
| | Hong Kong | HKG | HSI | 0,00 | 0,01 | (0,15) | 9,56 | 0,00 | 0,02 | (0,13) | 4,77 |
| | P. R. of China | CHN | SHSZ300 | 0,00 | 0,02 | (0,50) | 5,96 | 0,00 | 0,02 | (0,35) | 5,38 |
| | Taiwan | TWN | TWSE | 0,00 | 0,01 | (0,67) | 6,15 | 0,00 | 0,01 | (0,38) | 5,53 |
| | Rep. of Korea | KOR | KOSPI | 0,00 | 0,01 | (0,48) | 5,22 | 0,00 | 0,01 | (0,54) | 6,40 |
| | Australia | AUS | AS51 | 0,00 | 0,01 | (0,38) | 7,24 | (0,00) | 0,01 | (0,29) | 4,88 |
| | Vietnam | VNM | VN | 0,00 | 0,02 | (0,03) | 3,79 | 0,00 | 0,02 | (0,01) | 3,37 |
| | Malaysia | MYS | FBMKLCI | 0,00 | 0,01 | (2,05) | 24,29 | 0,00 | 0,01 | (0,01) | 4,67 |
| | Thailand | THA | SET | (0,00) | 0,01 | (1,61) | 36,76 | 0,00 | 0,01 | (0,23) | 5,38 |
| | Indonesia | IDN | JCI | 0,00 | 0,01 | (0,70) | 7,99 | 0,00 | 0,01 | (0,21) | 7,67 |
| | New Zealand | NZL | NZSE50FG | 0,00 | 0,01 | (0,08) | 3,91 | 0,00 | 0,01 | (0,45) | 4,84 |
| | Singapore | SGP | FSSTI | 0,00 | 0,01 | (0,43) | 6,01 | 0,00 | 0,01 | 0,29 | 5,65 |
| | Philippines | PHL | PCOMP | 0,00 | 0,01 | (0,25) | 7,65 | 0,00 | 0,01 | (0,16) | 5,41 |
| | Mongolia | MNG | MSETOP | 0,00 | 0,04 | 2,71 | 43,14 | 0,00 | 0,02 | 0,98 | 9,85 |
| South Asia [SAs] | Pakistan | PAK | KSE100 | 0,00 | 0,02 | (0,31) | 4,75 | 0,00 | 0,01 | (0,33) | 5,48 |
| | Sri Lanka | LKA | CSEALL | 0,00 | 0,01 | (1,00) | 17,41 | 0,00 | 0,01 | 0,37 | 6,52 |
| | India | IND | NIFTY | 0,00 | 0,02 | (0,43) | 5,93 | 0,00 | 0,02 | 1,11 | 16,05 |

Table 1. Basic information and statistics on selected stock indices. All stock indices (except Vietnam in the second period) rejected the null hypothesis of normality by means of Jarque-Bera test at the 5% confidence level. All statistics estimated on raw data (e.g. before standardization). [a] Based on World Bank's Lending Groups as of December 2015 (retrieved from http://data.worldbank.org/about/country-and-lending-groups). [b] ISO three-letter country code.

## 9 Appendix B. Calinski and Harabasz (1974) clustering validity index

Before GFC




After GFC

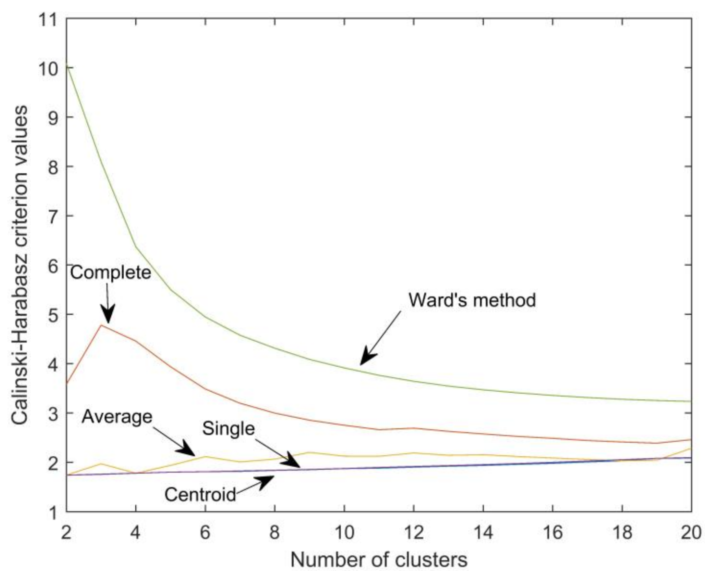
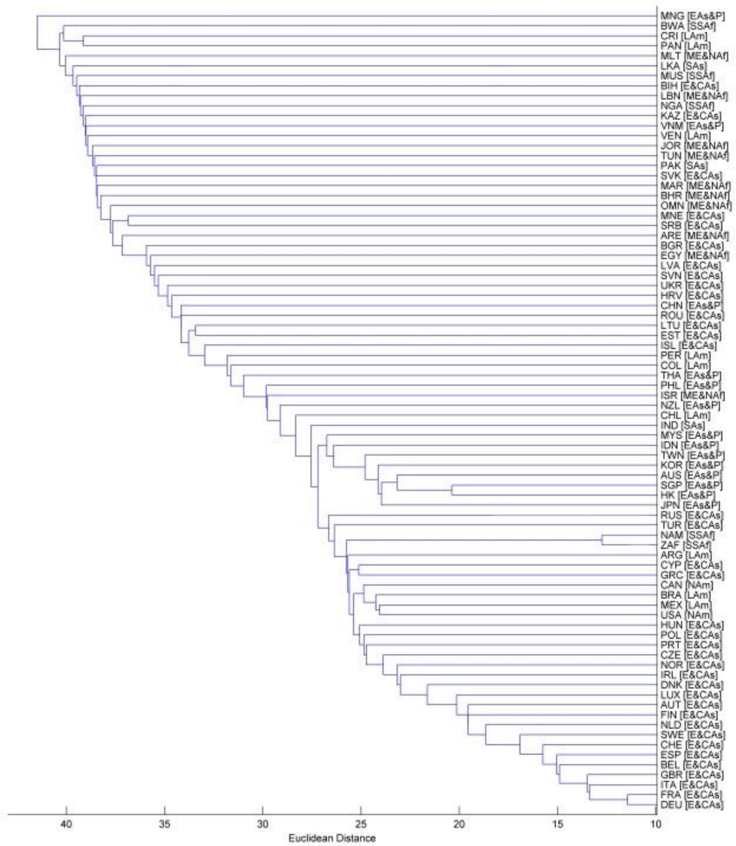



Figure 4. Calinski and Harabasz clustering validity index. It is calculated as the ratio of clusters' separation to compactness, which are measured as the between-cluster sum of squares and the within-cluster sum of squares, respectively. Well-defined clusters display large between-cluster sum of squares and small within-cluster sum of squares, thus the larger the index the better the clustering solution.

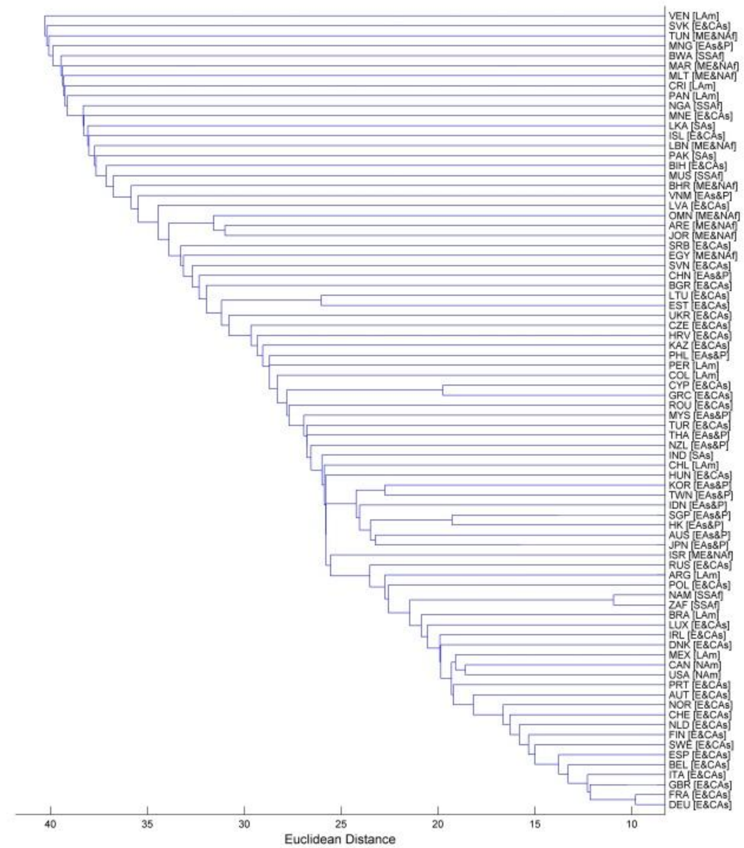
# 10 Appendix C. Dendrograms with other linkage methods

Single linkage

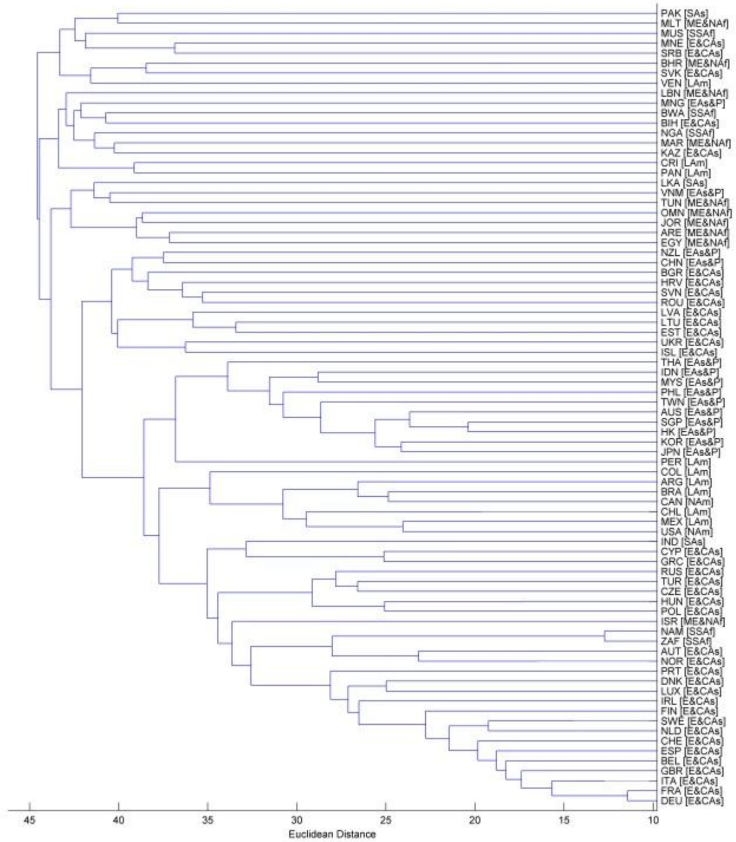
Before GFC

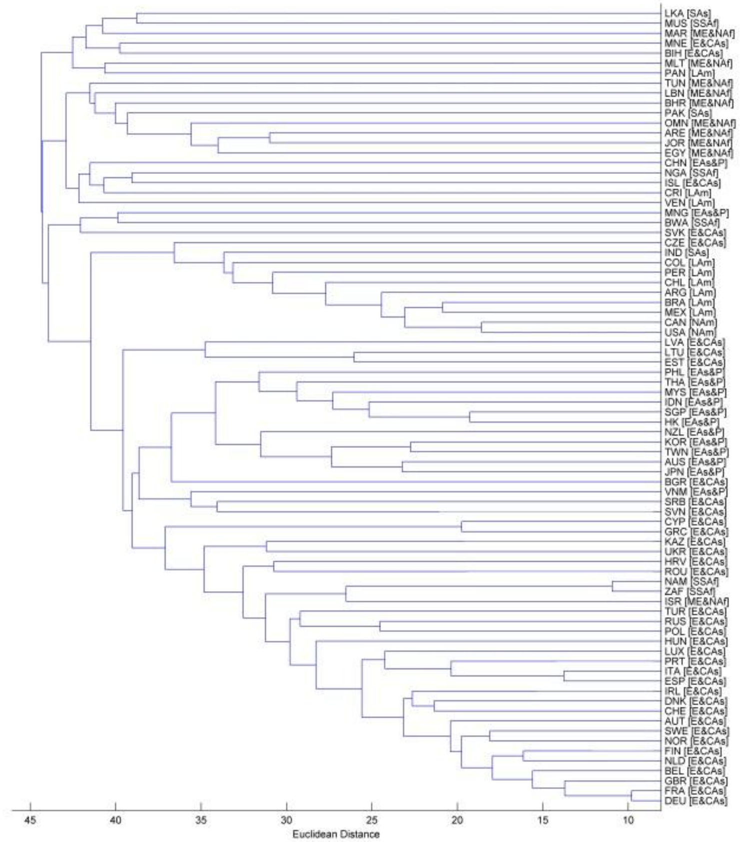



After GFC



Complete linkage



Average linkage

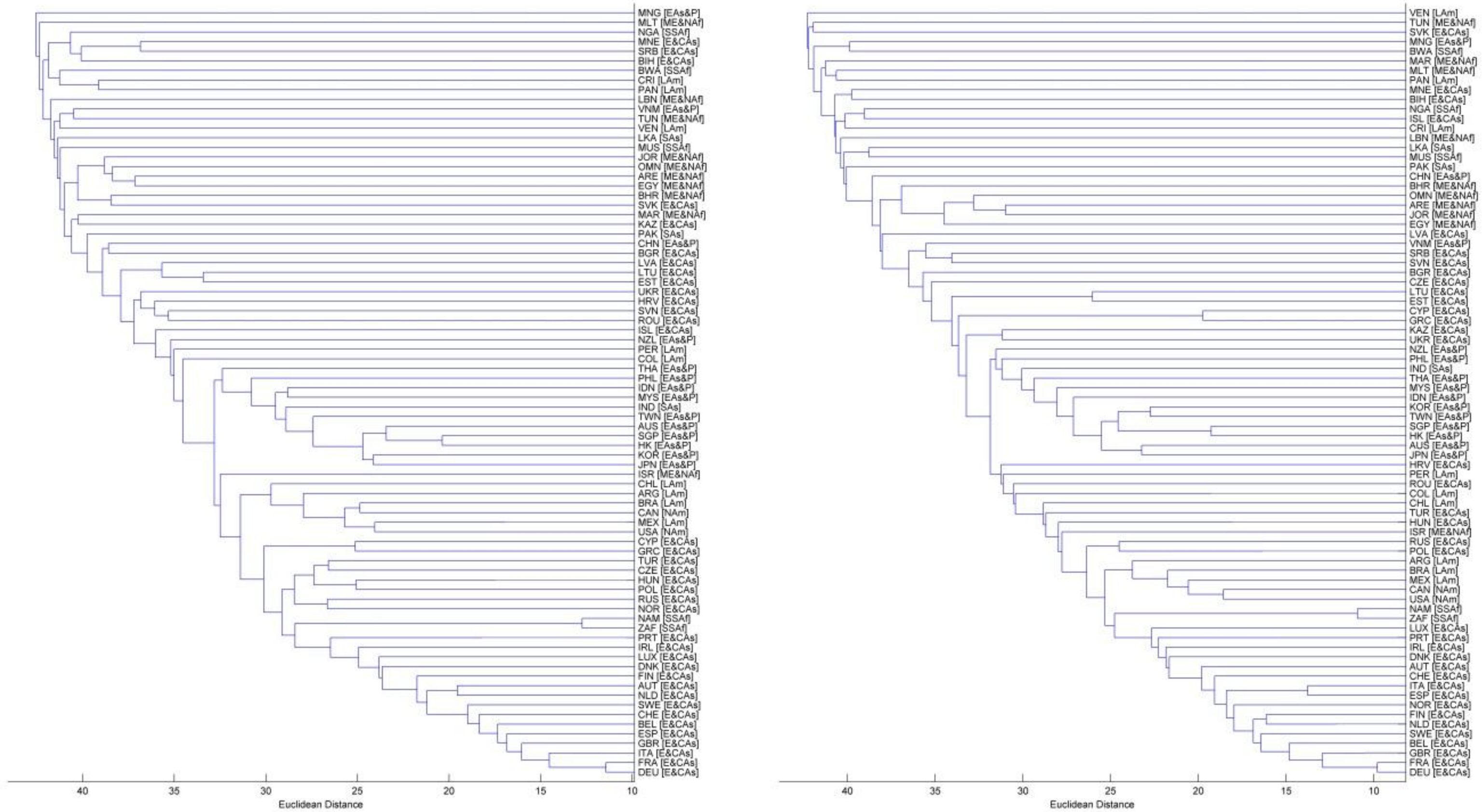



Figure 5. Dendrogram after and before the GFC, for single, complete, and average linkage methods. In brackets the region each country pertains to according to World Bank's Lending Groups: E&CAs (Europe & Central Asia), EA&P (East Asia & Pacific), ME&NAf (Middle East & North Africa), SAs (South Asia), SSAf (Sub Saharan Africa), LAm (Latin America), NAm (North America).